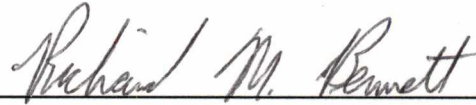


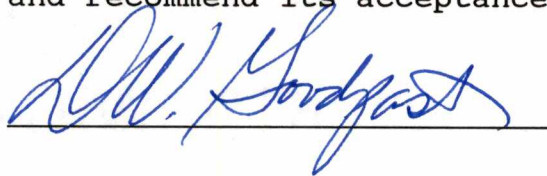
To the Graduate Council:

I am submitting herewith a thesis written by Rex D. Gilley entitled "Snow Load Modelling for Structural Load Combination Methods." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Civil Engineering.



Richard M. Bennett, Major Professor

We have read this thesis
and recommend its acceptance:



Accepted for the Council:



Associate Vice Chancellor
and Dean of The Graduate School

SNOW LOAD MODELLING
FOR
STRUCTURAL LOAD COMBINATION METHODS

A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Rex D. Gilley

December 1991

ACKNOWLEDGEMENTS

While attending the University of Tennessee, I have been surrounded with abundant expertise and inspiration. I would like to thank my wife for her patience, understanding, and perseverance during the last eighteen months. I am indebted to my major professor Dr. Richard M. Bennett who provided an endless knowledge base for my research endeavors as well as my coursework. I would also like to thank Dr. Edwin G. Burdette and Dr. David W. Goodpasture who served on my committee and provided encouragement throughout my graduate education.

I would like to thank the National Science Foundation for funding this project. This project could not have been completed without their support.

ABSTRACT

New methods of load combination analysis have been developed that describe more accurately the combined loads acting on structures. Present design codes using probability-based load factors have not evolved to the use of these new methods due to a lack of statistical data needed to describe the various load types.

Statistics of water equivalent ground snow load data were obtained for seventeen sites across the United States. These snow loads were modelled as a Poisson square wave pulse process. Daily water equivalent snow load intensity was fitted with a Weibull distribution. Verification of this distribution function was provided by comparison of predicted 50-year snow loads to well established 50-year snow loads.

Occurrence dependence, intensity and duration dependence, and intensity dependence were considered with respect to their effect on load combination analyses. The correlation of snow loads with other loads was also considered.

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CHAPTER 1

INTRODUCTION

Loads acting on all types of concrete, steel, and wood structures are of primary interest to structural engineers. For optimum design of these structures, it is imperative that the behavior of the various loads involved be understood. The maximum combined load occurring during the structure's lifetime is of significant importance as this load is used in the design of the individual members. Over a fifty year design life, each of the various loads will reach some maximum value, though probably not simultaneously. Combining the lifetime maximum values of each load will yield an upper limit to the maximum lifetime load. For the design of practical structures this upper limit is too conservative, hence the use of probability theory to develop appropriate load combinations.

Advances in the study of structural reliability have produced several design codes using probability-based load factors (ANSI A58.1-1982, ANSI/ASCE 7-88, AISC LRFD 1986, 1988 Prestandard Wood Code). However, inconsistencies still exist in the treatment of the load combination problem. For example, a lower reliability index may result when wind controls a design as opposed to earthquake controlling, while the opposite is desired (Wen and Kim, 1989). New load factors have been proposed using the load coincidence method to

overcome this deficiency (Wen, 1977). Lack of sufficient statistics to model loads as random processes has hindered progress. Corotis and Jaria (1979) suggested that assigning realistic values to the loads a structure may carry is the least precise phase of design. Pier and Cornell (1973) noted that structural behavior descriptions are more advanced than the probabilistic description of the loads acting on the structure. To continue the evolution of probability-based design codes by using more accurate structural reliability methods, we must have statistical data for the respective loads.

Factory Mutual Insurance Company reported that fifty-five percent of all roof losses that occurred from 1974 to 1978 on buildings they insured were due to snow loads (O'Rourke et al., 1982). Seventy-five percent of these losses were due to drift loads, twenty percent were due to uniform roof snow loads, and the remaining five percent were due to unsymmetric drift loads. These failures emphasize the need for understanding the behavior of snow loads.

Ellingwood and O'Rourke (1985) listed seven research areas that are needed regarding snow loads. Two of the seven research areas are "procedures for the probabilistic combination of snow loads with other loads" and "definition of parameters needed to model snow loads as random processes." Both of these areas are addressed in this research. Although considerable work has been done in the area of roof snow

loads, a void still exists regarding the modelling of ground snow loads as a Poisson square wave process. The modelling of ground snow loads will yield the values necessary for development of more accurate load combination analyses.

SNOW PROCESS

In general, availability of moisture in the atmosphere and mechanisms to convert the moisture into precipitation are the two factors governing the occurrence of precipitation. The vertical motion of air provides cooling which results in the conversion of moisture to precipitation in the atmosphere. Snow is defined as particles of ice formed in clouds that have grown large enough that they can fall, reaching the ground with measurable velocity. The moisture required is obtained by evaporation from oceans, lakes, rivers, soils, and plants due to a heat source such as the sun.

Snowcover includes snowfall, ice pellets, hoar frost, and water from rainfall all of which has jointly accumulated. The variability of this process depends upon the parent weather's variability (i.e. atmospheric wind, temperature, and moisture of air during precipitation and after deposition) and the nature and frequency of the parent process. Detailed discussions of these and other factors as well as other snow related engineering topics can be found in Gray and Male (1981).

LOAD MODELLING

The modified Turkstra's rule (Turkstra, 1970) is a common method for handling the load combination problem. Turkstra's rule takes the maximum combined load as the maximum of all permutations of one load at its lifetime maximum value, while taking all other loads at their arbitrary point-in-time values. This method was used by Ellingwood et al. (1982) to develop probability-based load factors that have been incorporated into the previously mentioned design specifications.

One weakness to Turkstra's rule is that it is always unconservative, although it performs acceptably well in many instances. Wen and Pearce (1981b) have found Turkstra's rule to be quite unconservative in certain situations. Ellingwood et al. (1980) used a yearly maximum snow load as the arbitrary point-in-time value in the load combination which is a conservative definition that serves to counteract the unconservative nature of Turkstra's rule. Lindsey (1988), a consulting engineer, has complained that the 0.5S load factor for arbitrary point-in-time snow loads is "a killer."

Pearce and Wen (1984), Larrabee and Cornell (1981), and Grigoriu (1984) have developed other methods for obtaining maximum combined load statistics. In general, these methods take the loads acting on structures as following a Poisson square wave pulse process as described in Chapter 3. A

clipped normal process has been proposed as an alternate load model (Ditlevsen and Madsen, 1983), though not used in this research.

Belk and Bennett (1988) developed statistics for winds modelled as a Poisson square wave pulse process, with comparisons to 50-year wind speeds developed by Simiu et al. (1979) provided. Statistics to describe sustained and extraordinary live loads as Poisson square wave models have been developed as well (McGuire and Cornell, 1974; Corotis and Tsay, 1983).

PREVIOUS ANALYSES

The following section gives an overview of other research that has been done in relation to snow loads.

Structural design codes handle snow loads by specifying a ground snow load and a ground-to-roof snow load conversion factor. Ground snow loads are specified by use of contour maps developed from numerous data sources (Sack, 1989). Ellingwood and Redfield (1983) examined water equivalent snow data at 76 sites and found a lognormal distribution to be an appropriate snow load model. Uniform snow loads were analyzed by O'Rourke et al. (1982) to obtain appropriate statistics for the ground-to-roof snow load conversion factors. Exposure, thermal, and roof slope effects were considered in determining the conversion factor. The conversion factors were found to

follow a lognormal distribution. Ghiocel and Lungu (1975) reference a conversion factor that is based on the average winter wind velocity, which accounts for the dependence of the conversion factor on exposure. Statistical data for ground snow loads and conversion factors were combined by O'Rourke and Stiefel (1983) to obtain N-year conversion factors for a given mean recurrence interval such as 25 or 50 years.

Drifted snow loads are also of importance as they cause the majority of structural failures due to snow loads. Templin and Schriever (1982) discussed the fluid mechanics of air flow around a structure that causes drifting. Snow is picked up in high wind areas and deposited in low wind areas, whereby the snow's accumulation and density increase, thus increasing the load.

O'Rourke et al. (1985) examined 350 case histories to determine appropriate parameters to describe drift formations on multilevel roofs. An empirical relationship was developed for drift formations in terms of roof elevation difference, upper and lower roof lengths, and ground snow load. The research was used to develop proposed code revisions by O'Rourke et al. (1986) and was incorporated into ANSI/ASCE 7-88. O'Rourke and Wood (1986) applied the theory of fluid flow over bluff bodies to snow drifts considering roof lengths, roof elevation difference, and roof widths as important variables.

Simulation techniques were used to develop a

probabilistic model for roof snow loads on sloping roofs for various roof slopes and materials by Sack et al. (1987). Sack (1988) considered such factors as building exposure, roof slope, thermal effects, and sliding of snow onto lower roofs in an investigation of "slippery" roofs. Taylor (1985) examined the effects of surface roughness and roof slope on snow accumulation on shed roofs in Ottawa, Canada.

Taylor (1980) gives an extensive review of Canadian code development pertaining to snow loads. Boyd (1961) examined ground snow depth data for 480 stations to develop 30-year mean recurrence interval snow depths for use in Canadian codes. Taylor (1979) discusses the application of roof snow data to ground-to-roof conversion factors for various curved and gabled arena roofs under symmetrical and unbalanced loads.

A roof snow load prediction model was developed by Isyumov (1982) considering such parameters as roof geometry, local shelter, and geographic and temporal variations. The model predicts snow load durations in addition to intensities. This model is useful for the time dependent behavior of wood, and it is equally important in the load combination problem.

Isyumov and Davenport (1974) used wind tunnel and water flume tests in a mass balance approach to obtaining a probabilistic snow load model. Correlation between occurrences of wind and snow were examined. It was found that daily mean and maximum hourly wind speeds were 15% and 18% higher, respectively, on days with snowfall.

An appropriate snow load was developed for combined snow and earthquake loads by O'Rourke et al. (1984). A design base shear with the same probability of being exceeded as the design peak ground acceleration was obtained for Buffalo and Stampede Pass. The Uniform Building Code (1988) specifies 25% of the design snow load for snow loads over 30 psf, which is considerably higher than the 2% and 13% found for Buffalo and Stampede Pass, respectively.

Turkstra and Madsen (1980) used a model that divides snow loads into continental and temperate loads for use in load combinations methods. The continental snow was assumed to follow an Extreme Type I distribution with a coefficient of variation of 0.25 and to occur once a year with a thirteen week duration. The temperate snow was assumed to follow a gamma distribution with a coefficient of variation of 0.5 and to occur thirteen times a year with a one week duration. The total snow load at any time is the sum of the continental and temperate snow load. Hendrickson et al. (1987) used this model to examine wood structural members.

OBJECTIVE AND SCOPE

The objective of this research was to obtain the statistics necessary to model daily water equivalent ground snow load as a Poisson square wave pulse process. Appropriate parameters are now available for use in load combination

analyses. An appropriate probability density function was fitted to the intensity data, with verification provided via comparison to well established 50-year snow loads. Occurrence dependence, intensity and duration dependence, and intensity dependence were examined. A preliminary discussion of the correlation of snow loads with other loads is provided.

CHAPTER 2

DATA COLLECTION

Ground snow loads are recorded in the United States by the National Weather Service, the Soil Conservation Service, state agencies, and others. The data used in this research is from yearly Climatological Data recorded by the National Oceanic and Atmospheric Administration. Actual snow data is recorded by NOAA when the snow depth is greater than or equal to two inches. The three forms of data recorded are snowfall for a given day, snow on the ground for a given day, and water equivalent snow depth. Snow depth to density relationships are highly variable (Ellingwood and O'Rourke, 1985; Ghiocel and Lungu, 1975; Taylor, 1980). Rather than use a "typical" specific gravity value to convert from snow depth to load, water equivalent snow depths yield a load directly resulting in more reliable data. Therefore, water equivalent snow load data are used throughout this research.

Codes generally specify a ground snow load for a given site with a conversion factor to obtain a design roof snow load. Ideally roof snow load data would be preferable; however, no sufficient data base exists. Therefore, ground snow load data are used in this research.

The duration of a given snow deposition is on the order of days as opposed to months. Therefore, daily ground snow loads provide a sufficiently fine enough time increment to

capture the temporal variability of snow loads.

Data for seventeen sites from across the continental United States were examined. Boston, Detroit, Columbia, Great Falls, Omaha, Rochester, Cleveland, and Green Bay were used as they were by Ellingwood et al. (1980) to develop current load factors. Omaha did not have sufficient data in the form needed; therefore, Valentine was used in its place. Buffalo and Stampede Pass were used since O'Rourke et al. (1984) examined them in combined earthquake and snow load analyses. Hendrickson et al. (1987) studied snow data for Minneapolis in the analysis of wood structural members, hence the use of Minneapolis in this research. Boise, Portland, Bismarck, Pendleton, and Casper were used in an attempt to give reasonable geographical representation of the remaining northern United States. Knoxville was used as a representation of southern U.S. snow data and for local interest. The geographical location of the seventeen sites is given in Figure 2.1.

Twenty years of daily water equivalent ground snow data starting with January, 1970 were recorded for fourteen sites. Twelve years of continuous data were available for Columbia starting with January, 1970. No water equivalent data were available for Valentine for 1970; therefore, the data collected for this site were from January, 1971 through December, 1989. Data for Stampede Pass were collected for January, 1970 through March, 1989.

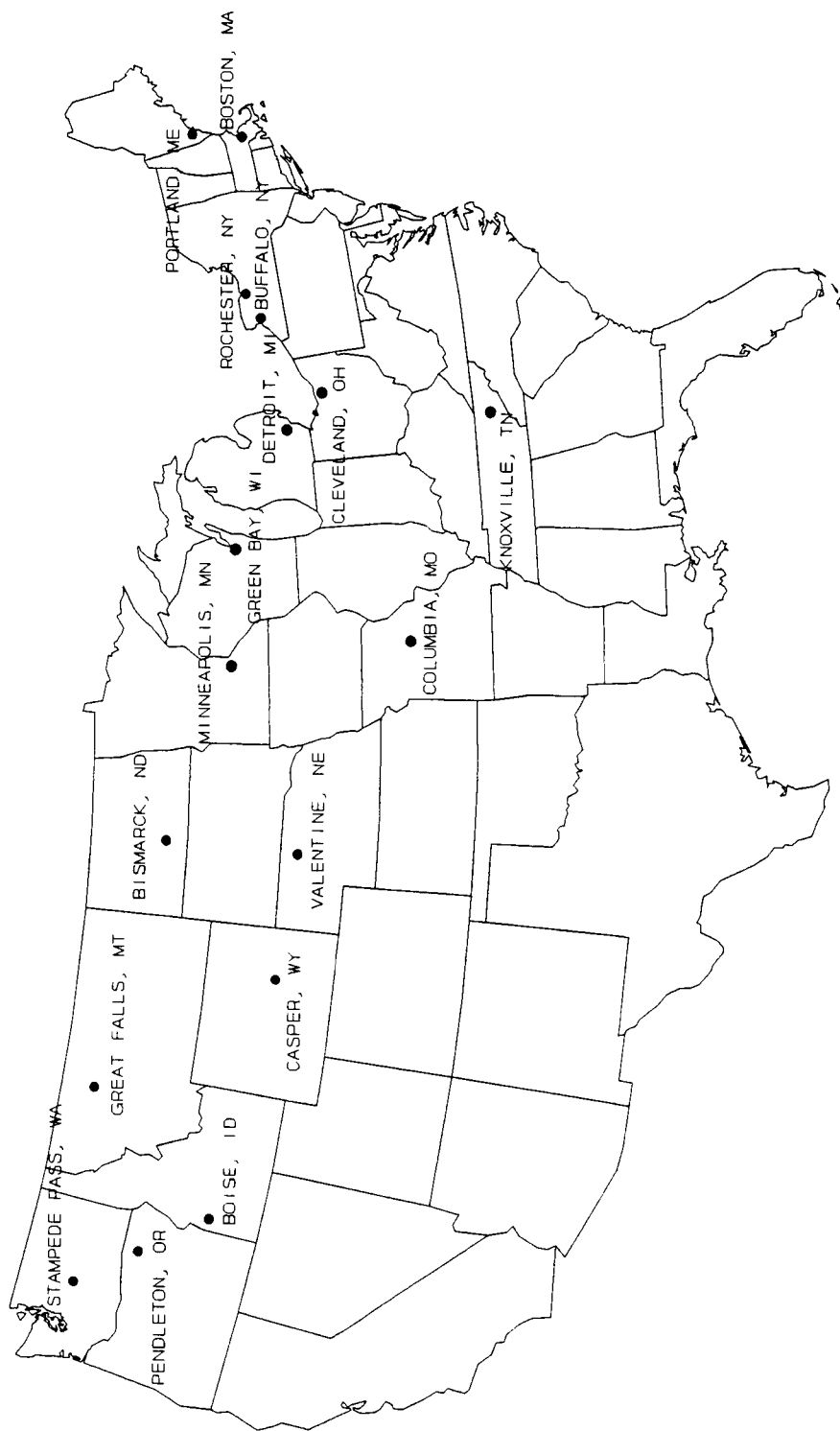


Figure 2.1 Sites Analyzed.

CHAPTER 3

DATA REDUCTION

A flexible model that has been widely used to model time varying loads is the Poisson pulse process. It is characterized by a mean occurrence rate λ , a mean load duration, and a random intensity (Wen and Pearce, 1981a; Wen, 1981). Figure 3.1 is an example of a Poisson square wave pulse process with variables as shown. The width of each Poisson square pulse is represented by the duration of the occurrence, while intensity of the occurrence represents the height of each pulse. Time lag is defined as the time lapse between the beginning of one occurrence and the beginning of the next occurrence and is the reciprocal of the rate of occurrence.

The clustering of loads around a common point can also be handled by a Poisson square wave process. Figure 3.1 shows a single occurrence as well as a clustered occurrence. Time lag and duration of a clustered occurrence are defined the same as for a single occurrence. Within a given clustered occurrence, individual random durations and intensities exist for each single occurrence that makes up the clustered occurrence.

After collecting all of the daily water equivalent snow data for each city, the data was then entered into a statistical analysis program (STATGRAPHICS 4.0, 1989). Intensity of each occurrence, duration of each occurrence,

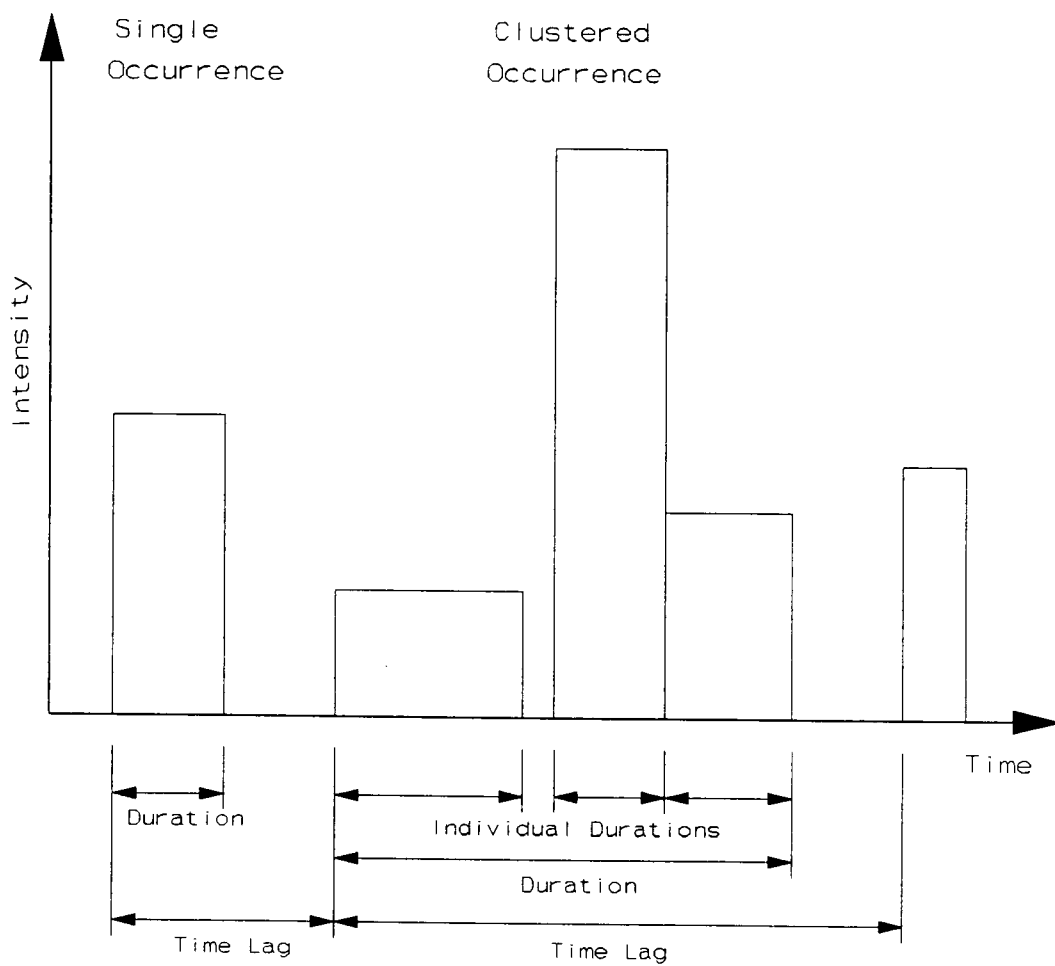


Figure 3.1 Poisson Square Wave Pulse Process.

time lag between occurrences, cluster duration, and the number of individual occurrences within a cluster were the five variables used.

Although sufficient data exists to model each day as a single occurrence, each set of data is represented by a model envelope encompassing several days, similar to Hendrickson et al. (1987). Figure 3.2 shows the actual data for Rochester from January 1 to March 4, 1970 as well as the Poisson square wave model envelope. Due to the subjectivity of the data model, a maximum intensity within an occurrence was used rather than an average intensity as shown in Figure 3.2.

All other variables were entered into the computer program according to their definitions given previously and as shown in Figure 3.1. Pertinent statistics for use in subsequent calculations were obtained for all variables. Table 3.1 gives mean and standard deviation values for intensity in inches of water and duration in days of each individual occurrence for each city. Table 3.2 gives mean and standard deviation values for time lag, cluster duration, and the number of individual occurrences within a cluster for all sites. Values for the reciprocal of time lag are given as average number of occurrences per year in Table 3.3.

Another characteristic value of interest is the product of the mean rate of occurrence and mean cluster duration (Table 3.3). This product represents the fraction of the time that the process is non-zero or 'on'. Except for Knoxville,

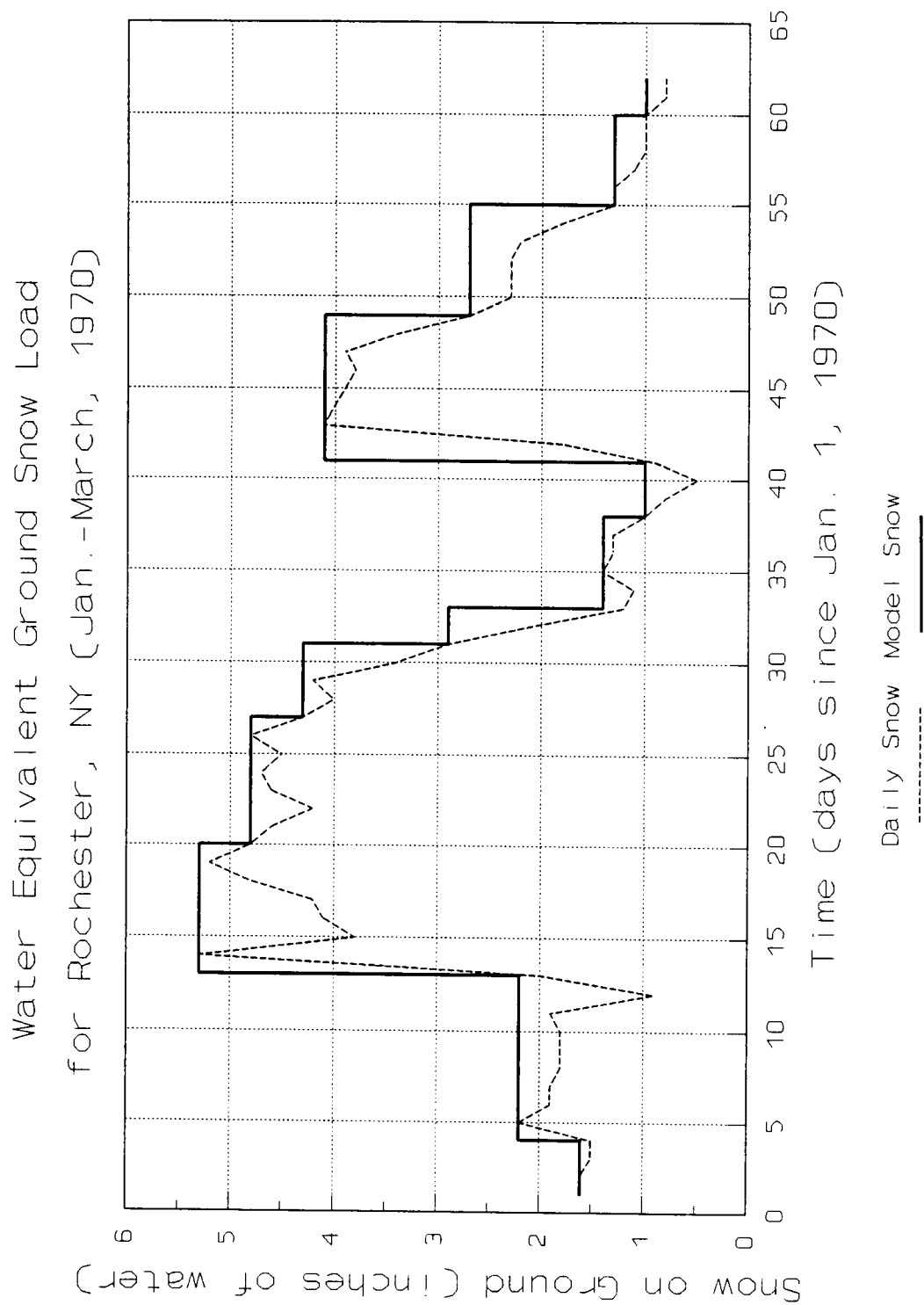


Figure 3.2 Example Data for Rochester, NY.

Table 3.1

Reduced Data for Individual Occurrences

Location	Sample Size	Intensity (in. water)		Duration (days)	
		Mean	S.D.	Mean	S.D.
Boise	95	0.57	0.43	4.26	3.22
Portland	371	2.29	2.18	3.79	2.47
Boston	197	1.23	1.31	2.62	1.54
Detroit	240	0.86	0.83	3.21	2.11
Minneapolis	397	1.70	1.13	4.49	3.30
Columbia	109	0.94	0.76	2.61	1.33
Great Falls	338	0.66	0.57	2.91	1.78
Valentine	184	0.90	0.87	3.79	2.74
Buffalo	277	1.40	1.46	4.21	2.88
Rochester	276	1.12	1.09	4.43	2.89
Bismarck	241	1.22	1.08	6.11	4.46
Cleveland	188	0.79	0.81	4.18	2.80
Pendleton	79	0.55	0.41	3.96	3.15
Knoxville	34	0.42	0.25	2.41	1.13
Stampede Pass	588	22.50	17.19	6.88	6.28
Green Bay	277	1.58	1.39	5.53	3.33
Casper	273	0.37	0.30	3.24	2.15

Table 3.2

Reduced Data for Clustered Occurrences

Location	Sample Size	Time Lag (days)		Cluster Duration (days)		Number in Cluster	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Boise	40	156.38	155.79	10.48	14.39	2.38	2.57
Portland	80	90.94	115.19	17.63	25.44	4.64	6.20
Boston	85	86.02	117.16	6.08	9.71	2.32	3.11
Detroit	98	74.19	105.42	7.94	11.81	2.45	3.33
Minneapolis	63	113.86	120.99	28.40	38.90	6.30	8.18
Columbia	43	94.07	133.11	6.72	10.47	2.53	3.49
Great Falls	151	46.48	62.56	6.66	9.97	2.24	2.70
Valentine	79	84.13	102.09	8.92	16.14	2.33	3.19
Buffalo	127	55.68	86.24	9.31	15.72	2.18	2.84
Rochester	128	56.19	90.26	9.72	16.13	2.16	2.70
Bismarck	75	95.32	105.30	19.73	30.57	3.21	4.38
Cleveland	113	64.45	97.30	7.04	10.10	1.66	1.58
Pendleton	52	128.69	161.49	6.02	9.00	1.52	1.18
Knoxville	29	238.31	303.37	2.86	1.85	1.17	0.38
Stampede Pass	51	130.43	143.26	77.27	93.02	14.53	13.37
Green Bay	78	90.03	111.64	19.76	29.33	3.55	4.53
Casper	192	37.86	57.09	4.68	5.34	1.42	0.96

Table 3.3

Mean Rates of Occurrence and Product of Rates
of Occurrence and Cluster Duration

City	Average # of occurr. per year	Rate of occurr. * Cluster Duration
Boise	2.33	0.07
Portland	4.01	0.19
Boston	4.24	0.07
Detroit	4.92	0.11
Minneapolis	3.21	0.25
Columbia	3.88	0.07
Great Falls	7.88	0.14
Valentine	4.34	0.11
Buffalo	6.56	0.17
Rochester	6.50	0.17
Bismarck	3.83	0.21
Cleveland	5.66	0.11
Pendleton	2.84	0.05
Knoxville	1.53	0.01
Stampede Pass	2.80	0.60
Green Bay	4.05	0.22
Casper	9.64	0.12

the products given show that snow loads do not behave transiently, i.e. the product is not less than 0.015 (Wen, 1990). This data gives physical meaning to the snow load process. For example, the average number of occurrences per year for Stampede Pass is the third lowest; however, the product of the occurrence rate and cluster duration indicates that snow occurs approximately 220 days out of the year at this site.

Sample size indicates the total number of occurrences for either individual or clustered occurrences over the time span of the data collection. Confidence intervals for a given sample size can be approximately calculated. A 90% central confidence interval on the mean is $\pm 15\%$ for a sample size of 115, $\pm 20\%$ for a sample size of 60, $\pm 25\%$ for a sample size of 38, and $\pm 30\%$ for a sample size of 25 (Sachs, 1984). The clustered data presented provide a 90% confidence interval of $\pm 20\%$ for twelve sites, while the given unclustered data provide a confidence interval of $\pm 20\%$ for sixteen sites. As might be expected, the 90% confidence interval for Knoxville was $\pm 26\%$ indicating that more years of data are needed due to the sparse snowfall. In general twenty years of data are sufficient to obtain macro time characteristics, although some sites may warrant additional data.

Examination of these tables shows the geographical variation of snow deposition in the United States. Knoxville being representative of the south shows that complete melting

occurs between snowfalls with a mean number of loads per cluster near one. On the other extreme, Stampede Pass has complete snow cover for eight to nine months out of the year with a mean number of loads per cluster of 14.53.

CHAPTER 4

DATA ANALYSIS

Design codes specify a ground snow load for the site of interest when designing a structure. This ground snow load has a mean recurrence interval (mri) of 50 years for ANSI A58.1-1982 and ANSI/ASCE 7-88, while the National Building Code of Canada (1989) uses a 30 year mri. A 50 year mri corresponds to an annual probability of being exceeded of two percent (0.02). The use of ground snow loads in formulating design roof snow loads requires fitting ground snow load data with an appropriate cumulative distribution function (cdf). The cdf can in turn be used to predict future snow loads for use in design.

Previous analyses have primarily dealt with design snow loads and the fitting of a cdf to annual extreme snow data. Thom (1966) fitted a lognormal distribution to annual maxima water equivalent ground snow data as did Tobiasson and Redfield (1983). Ellingwood and Redfield (1983) found a lognormal distribution to be the best overall fit to annual maxima water equivalent ground snow loads at 76 sites in the northeast United States. Other cumulative distribution functions that have been fitted to annual maxima ground snow loads are Frechet (type II), log Pearson type III, and Gumbel (type I) (Sack, 1989). Daily ground snow data analyzed by Isyumov and Davenport (1974) showed that a Weibull

distribution was suitable for four Canadian cities.

The present study attempts to fit a cdf to the intensity of individual snow occurrences for twenty years of continuous data, typically, for each city. The distribution functions examined for fitting the frequency distribution of the intensity of snowfall for each site are lognormal, Extreme Type I, Extreme Type II, Weibull, gamma, and Erlang. The Weibull distribution performed the best with the gamma distribution being a close second. The Extreme Type I and Erlang distributions performed somewhat less effectively. The lognormal and Extreme Type II distributions provided the poorest fit to the data. The specific performance of each distribution function will be discussed in Chapter 5.

OCCURRENCE DEPENDENCE

To verify the use of a Poisson process in modelling the temporal characteristics of snow loads, the ratio of the variance to the mean for the number of occurrences needs to be obtained. For a Poisson process this ratio should be near one. The number of new individual occurrences per week was tabulated and the mean and variance calculated for all sites. The values in Table 4.1 for unclustered occurrences indicate that the occurrence of snow follows a compound Poisson process (Sachs, 1984). In other words, when one snowfall occurs several other occurrences are likely to follow. Wen and

Table 4.1

Ratio of Variance to Mean for Number of Occurrences per Week

City	Unclustered	Clustered
Boise	1.44	1.06
Portland	1.64	1.00
Boston	1.78	0.95
Detroit	1.51	0.93
Minneapolis	1.44	0.94
Columbia	1.85	0.93
Great Falls	1.47	1.00
Valentine	1.49	0.92
Buffalo	1.16	0.94
Rochester	1.17	0.93
Bismarck	1.11	0.96
Cleveland	1.14	0.93
Pendleton	1.13	0.95
Knoxville	1.14	0.97
Stampede Pass	0.86	0.95
Green Bay	1.13	0.98
Casper	1.05	0.88

Pearce (1981a) refer to this behavior as occurrence dependence or clustering. A negative binomial distribution would be more appropriate than the Poisson distribution in this case (Sachs, 1984).

To take clustering into account, occurrences that were immediately adjacent to one another or within one day of each other were taken to act jointly as a cluster of occurrences. The total number of clustered occurrences was tabulated from which the variance and mean were calculated. The ratio for clustered occurrences for all sites is given in Table 4.1. Except for Casper, this ratio falls within the range of 9/10 and 10/9 recommended by Sachs (1984) to consider a process a Poisson process.

These results indicate that the clustered Poisson process developed by Wen and Pearce (1981a) is appropriate for modelling snow loads for use in load combination analyses. Figure 3.1 represents this model with all parameters discussed previously.

INTENSITY AND DURATION DEPENDENCE

Dependence between intensity and individual duration is an important correlation aspect as well. This correlation can be measured in terms of a correlation coefficient. Values of the correlation coefficient for all sites are given in Table 4.2. Note that Knoxville's correlation coefficient is rather

Table 4.2

**Correlation Coefficients for Intensity vs.
Individual Duration**

City	Correlation Coefficient
Boise	0.30
Portland	0.10
Boston	0.01
Detroit	-0.03
Minneapolis	0.05
Columbia	0.16
Great Falls	0.11
Valentine	0.12
Buffalo	0.32
Rochester	0.27
Bismarck	0.05
Cleveland	0.28
Pendleton	0.32
Knoxville	0.44
Stampede Pass	0.18
Green Bay	0.09
Casper	0.21

high in comparison to other cities. Typically, snow melts between occurrences in southern U.S. cities, hence no accumulation between occurrences. Thus, if a heavy snowfall occurs, it will take longer to melt resulting in a longer duration. From a practical standpoint, correlation coefficients less than 0.5 have little effect on load combination analyses (Wen and Pearce, 1981a). Neglecting the effect of this correlation results in simplification of the Poisson square wave model. Due to the correlation being only slight, it seems within reason to ignore the correlation between intensity and duration in load combinations involving snow loads.

INTENSITY DEPENDENCE

A third dependence aspect of importance is intensity dependence between snowfalls. For a snow process it seems reasonable to assume that no intensity dependence exists between clustered occurrences. This assumption was verified by calculating a correlation coefficient between subsequent first snowfalls for each cluster at each of three sites. The correlation coefficients for Portland, Detroit, and Rochester were -0.08, -0.04, and 0.19, respectively. These values are certainly low enough to support the assumption of independence.

Dependence of intensity within individual clusters was

considered next. Two data sets were developed containing snowfall intensity for clustered occurrences with the correlation of an individual snowfall intensity to the following individual snowfall intensity within the cluster being of interest. The correlation coefficients for within cluster intensity dependence are relatively high. Correlation coefficients and their respective sample size are given in Table 4.3 for each site. The lowest coefficient is above 0.5, while the average for all sites is 0.77. Hence, intensity dependence within clusters should be considered in load combination analyses.

Table 4.3**Correlation Coefficients for Intensity
Dependence within Clusters**

City	Sample Size	Correlation Coefficient
Boise	55	0.72
Portland	291	0.94
Boston	112	0.75
Detroit	142	0.66
Minneapolis	334	0.87
Columbia	66	0.91
Great Falls	187	0.73
Valentine	105	0.82
Buffalo	150	0.79
Rochester	148	0.70
Bismarck	166	0.83
Cleveland	75	0.72
Pendleton	27	0.66
Knoxville	5	0.92
Stampede Pass	537	0.96
Green Bay	199	0.59
Casper	81	0.58

CHAPTER 5

VERIFICATION OF RESULTS

Two methods for determining the most appropriate probability distribution to model individual intensity were incorporated into this research. Chi-square values were tabulated for each probability distribution for all sites. Also, each probability distribution was used to generate a 50-year snow load that was compared to ASCE 7-88 50-year snow loads. Lognormal, Extreme Type I and II, Weibull, gamma, and Erlang distribution functions were examined.

A lognormal probability density function has the form that follows (Ang and Tang, 1975):

$$f_x(x) = \frac{1}{\sqrt{2\pi}\zeta x} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \lambda}{\zeta}\right)^2\right]$$

$$\lambda = \ln \frac{\mu}{\sqrt{1+\delta^2}} \quad (5.1)$$

$$\zeta^2 = \ln(1+\delta^2)$$

in which μ is the mean, δ is the coefficient of variation, and σ is the standard deviation in this and subsequent equations. An Extreme Type I probability density function has the form (Ang and Tang, 1984):

$$f_x(x) = \alpha e^{-\alpha(x-u)} \exp[-e^{-\alpha(x-u)}]$$

$$\alpha = \frac{\pi}{\sqrt{6}\sigma} \quad (5.2)$$

$$u = \mu - \frac{0.577215}{\alpha}$$

An Extreme Type II probability density function has the form (Ang and Tang, 1984):

$$f_x(x) = \frac{k}{v} \left(\frac{v}{x} \right)^{k+1} \exp \left[- \left(\frac{v}{x} \right)^k \right]$$

$$v = \frac{\mu}{\Gamma \left(1 - \frac{1}{k} \right)}$$
(5.3)

$$\delta = \frac{\left[\Gamma \left(1 - \frac{2}{k} \right) - \Gamma^2 \left(1 - \frac{1}{k} \right) \right]^{\frac{1}{2}}}{\Gamma \left(1 - \frac{1}{k} \right)}$$

in which $\Gamma(\cdot)$ is the gamma function. The gamma probability density function has the form (Ang and Tang, 1975):

$$f_x(x) = \frac{v (vx)^{k-1}}{(k-1)!} e^{-vx}$$

$$v = \frac{\mu}{\sigma^2}$$

$$k = \frac{\mu^2}{\sigma^2}$$
(5.4)

The Erlang probability density function is Equation 5.4 with k equal to an integer. The Weibull probability density function has the following form (Ang and Tang, 1984):

$$f_x(x) = \frac{k}{w-\epsilon} \left(\frac{x-\epsilon}{w-\epsilon} \right)^{k-1} \exp \left[- \left(\frac{x-\epsilon}{w-\epsilon} \right)^k \right]$$
(5.5)

w =characteristic smallest value
 k =shape paramater
 ϵ =lower limit (i.e. zero)

CHI-SQUARE TEST

To determine the validity of each of the six assumed distribution functions, chi-square goodness-of-fit values were calculated for each distribution function at each site. These values are tabulated in Table 5.1, where the superscript "a" indicates the distribution that performed best at a given site. Average chi-square values are given for each distribution function as well. The gamma distribution performed the best overall from the viewpoint that it had the lowest average chi-square value. However, this distribution never performed the best for any given site. The Weibull distribution performed second best on average, with four sites showing preference to this distribution. The Erlang distribution performed similar to the Weibull distribution on average and had four preferential sites as well. The lognormal distribution performed the best at eight sites; however, on average it was considerably higher than the three previous distributions. The Extreme Type I distribution was higher on average than the previous distributions. The Extreme Type II distribution was even higher; hence, the results are not tabulated. Figure 5.1 shows the performance of the various distribution functions for the frequency distribution of the intensity for Rochester, NY.

Distributions Fitted to Snowfall Intensity for Rochester, NY (Jan., 1970-Dec., 1989)

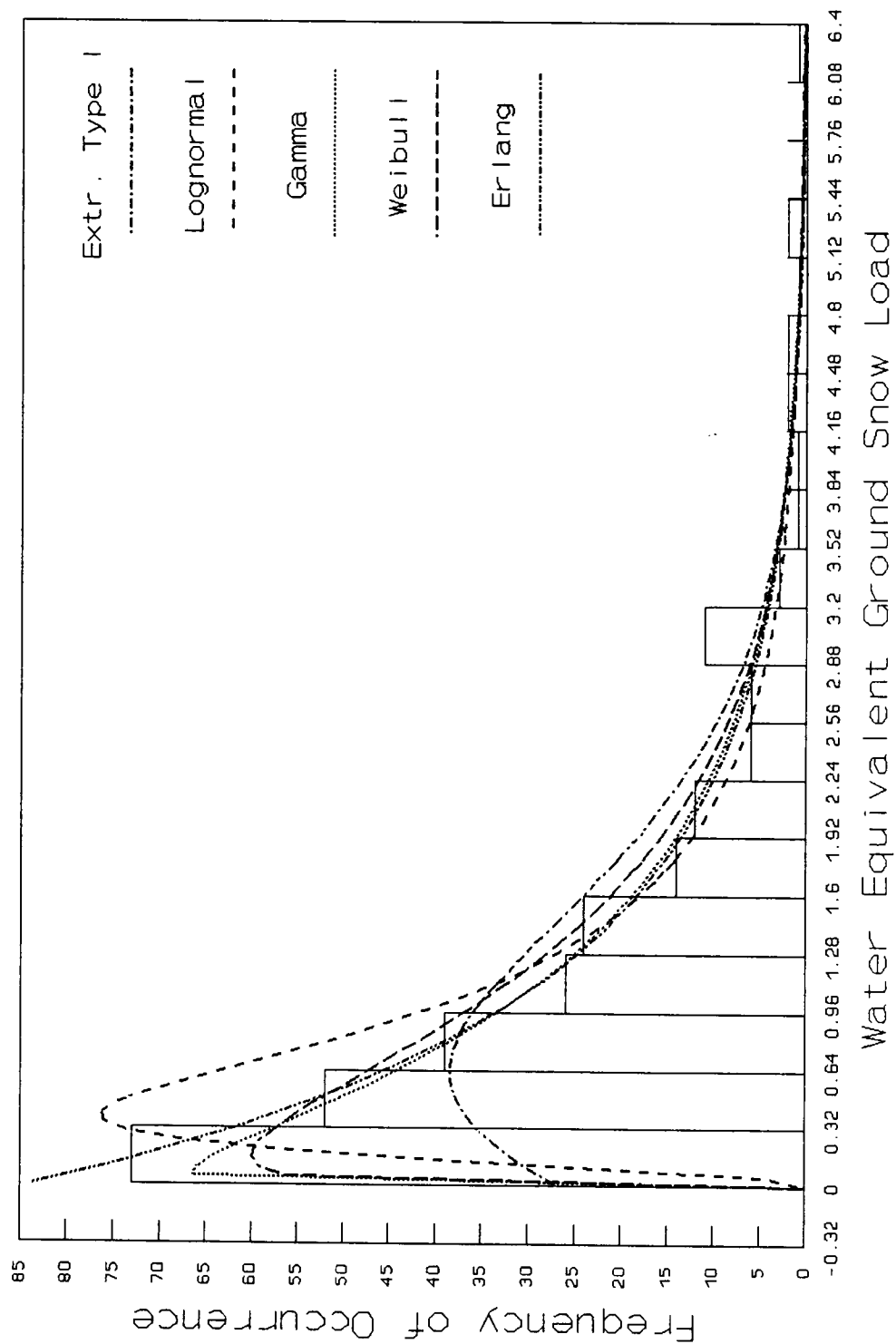


Figure 5.1 Various Distributions of Snowfall Intensity for Rochester, NY.

Table 5.1

Chi-square Values for Various
Probability Distribution Functions

Location	Log-normal	Extr. Type I	Weibull	Gamma	Erlang
Boise	16.62	12.27 ^a	14.99	13.15	13.25
Portland	98.44	207.28	96.13	96.49	94.97 ^a
Boston	6.74	25.30	4.60	6.96	4.55 ^a
Detroit	11.63 ^a	22.34	29.41	15.08	26.45
Minneapolis	121.72	87.98	52.82 ^a	64.66	69.91
Columbia	6.14 ^a	16.02	12.09	10.86	13.47
Great Falls	20.58 ^a	104.40	58.29	44.65	42.33
Valentine	12.23 ^a	25.98	29.52	21.07	28.29
Buffalo	30.71	34.84	22.84	28.10	18.40 ^a
Rochester	15.28	18.49	10.03	11.17	5.17 ^a
Bismarck	17.53	28.51	13.27 ^a	14.63	22.16
Cleveland	12.79 ^a	26.07	32.38	31.60	32.59
Pendleton	11.98 ^a	12.31	15.46	12.52	13.07
Knoxville	1.71 ^a	2.10	3.09	2.76	2.71
Stampede Pass	211.38	84.04	68.34 ^a	76.31	82.80
Green Bay	30.38	30.29	4.13 ^a	5.47	13.80
Casper	26.49 ^a	79.75	60.40	40.88	45.62
Average	38.37	48.12	31.05	29.20	31.15

^aIndicates the distribution function that performed best for a given site.

COMPARISON TO ASCE 7-88 STANDARD

Comparison of 50-year snow load predictions from daily snow data to 50-year snow loads developed from yearly extreme snow data provides another method for choosing an appropriate probability distribution function for modelling daily snow data. The 50-year snow load is the snow load that has a probability of being exceeded in one year of $1/50=0.02$. Values of 50-year snow loads are tabulated in a number of codes, including the ASCE 7-88 Standard.

The probability of a load exceeding a value x in a year is obtained by the load coincidence method of load combinations as (Wen, 1977; Wen, 1990)

$$P(X \geq x) = 1 - e^{-\nu t} \quad (5.6)$$

in which ν is the mean upcrossing rate of the combined load process above the threshold level x and t is time (365 days). The mean upcrossing rate for a single clustered load process is (Wen and Pearce, 1981a)

$$\nu = \lambda_c \frac{nG(x)}{nG(x) + 1} \quad (5.7)$$

where λ_c is the mean rate of occurrence of clusters, n is the mean number of loads per cluster, and $G(x)$ is the probability of an individual load exceeding x (i.e. 1-cumulative distribution function). The 50-year snow load can be obtained by setting Equation 5.6 equal to 0.02 and solving for x .

The appropriate parameters were used in conjunction with each distribution function to predict a 50-year snow load. The calculated values are given in Table 5.2 as well as ASCE 7-88 50-year snow loads. Table 5.3 gives the percentage that each of the predicted values differ from the ASCE Standard. Taking an average of the absolute values indicates a Weibull distribution as being most appropriate. Also, the Weibull distribution performed the best at four sites. A straight average indicates the Weibull distribution tends to overpredict the 50-year snow load by about ten percent.

The Extreme Type I distribution performed similar to the Weibull distribution and performed best at five sites. The gamma and Erlang distributions are next lowest with four and two cities, respectively, showing preference to these distributions. The lognormal and Extreme Type II distributions performed poorest with only one city each showing preference to them. Extreme Type II values do not appear in Tables 5.2 and 5.3 due to the degree which they are off the other values or ASCE Standard.

The Weibull distribution appears to perform the best at predicting 50-year snow loads from daily snow data with eleven of seventeen sites being within 25% of the ASCE Standard values. Chi-square tests also indicate that the Weibull distribution is an appropriate distribution for modelling daily snow intensity. Therefore, it is suggested that the Weibull distribution be used to model individual intensity.

Table 5.2

Comparison of Distribution Functions to 50-year Snow Loads
ASCE 7-88 (inches of water)

Location	ASCE	Log-normal	Extr. Type I	Weibull	Gamma	Erlang
Boise	1.15	2.77	2.27	2.13	2.23	2.23
Portland	11.92	19.39	12.88	14.76	14.77	15.63
Boston	5.77	10.25	6.97	6.40	6.22	7.63
Detroit	3.27	6.67	4.61	4.40	4.35	5.49
Minneapolis	9.62	9.18	7.27	6.94	8.41	7.83
Columbia	4.04	5.58	4.26	4.19	4.49	3.96
Great Falls	3.08	4.86	3.40	3.12	3.18	2.98
Valentine	4.23	6.74	4.73	4.61	4.53	5.56
Buffalo	8.08	12.56	8.22	8.52	8.33	9.20
Rochester	7.31	9.10	6.17	6.27	6.27	7.32
Bismarck	4.81	8.56	6.13	6.17	6.39	7.81
Cleveland	3.08	6.20	4.29	4.04	3.88	4.82
Pendleton	2.12	2.50	2.09	2.55	2.09	2.07
Knoxville	1.54	1.25	1.17	1.06	1.03	1.04
Stampede Pass	98.27	166.4	116.62	96.55	156.54	170.98
Green Bay	6.92	11.42	8.09	7.83	8.23	10.41
Casper	1.92	2.38	1.77	1.55	1.55	1.64

Table 5.3

Distribution Functions - Percentage off ASCE 7-88 Standard

Location	Log-normal	Extr. Type I	Weibull	Gamma	Erlang
Boise	140.8	97.4	85.0 ^a	94.3	93.7
Portland	62.7	8.1 ^a	23.8	23.9	31.1
Boston	77.7	20.8	10.8	7.8 ^a	32.2
Detroit	103.9	41.0	34.6	33.0 ^a	67.7
Minneapolis	-4.6 ^a	-24.4	-27.8	-12.6	-18.6
Columbia	38.0	5.4	3.7	11.1	-1.9 ^a
Great Falls	57.7	10.4	1.4 ^a	3.4	-3.2
Valentine	59.4	11.8	9.0	7.2 ^a	31.4
Buffalo	55.5	1.7 ^a	5.4	3.1	13.9
Rochester	24.5	-15.6	-14.2	-14.2	0.1 ^a
Bismarck	78.0	27.4 ^a	28.4	32.9	62.3
Cleveland	101.4	39.3	31.1	25.9 ^a	56.6
Pendleton	18.0	-1.2 ^a	20.2	-1.6	-2.4
Knoxville ^b	-19.0	-24.3	-31.2	-32.9	-32.6
Stampede Pass	69.4	18.7	-1.8 ^a	59.3	74.0
Green Bay	65.1	16.9	13.2 ^a	19.0	50.4
Casper	24.0	-7.8 ^a	-19.3	-19.2	-14.4
Av.Ab. Values	58.8	21.9	21.2	23.6	34.5
Straight Avg.	56.0	13.3	10.1	14.1	25.9

^aIndicates the distribution function that performed best for a given site.

^bExtreme Type II distribution function performed best for this site.

CHAPTER 6

CORRELATION WITH OTHER LOADS

Wen and Pearce (1981a) have shown that dependence between loads is a very important aspect of the load combination problem. Unconservative results may be obtained in load combination analyses when the intra-load dependence is ignored. Hence, correlation of snow loads with other loads needs to be considered. Snow loads are considered to be independent of live and earthquake loads. Two correlations of interest are the dependence between snow and wind loads and snow and rainwater loads. Methods of accounting for these intra-load dependencies are discussed and examples of actual occurrences are given in this chapter.

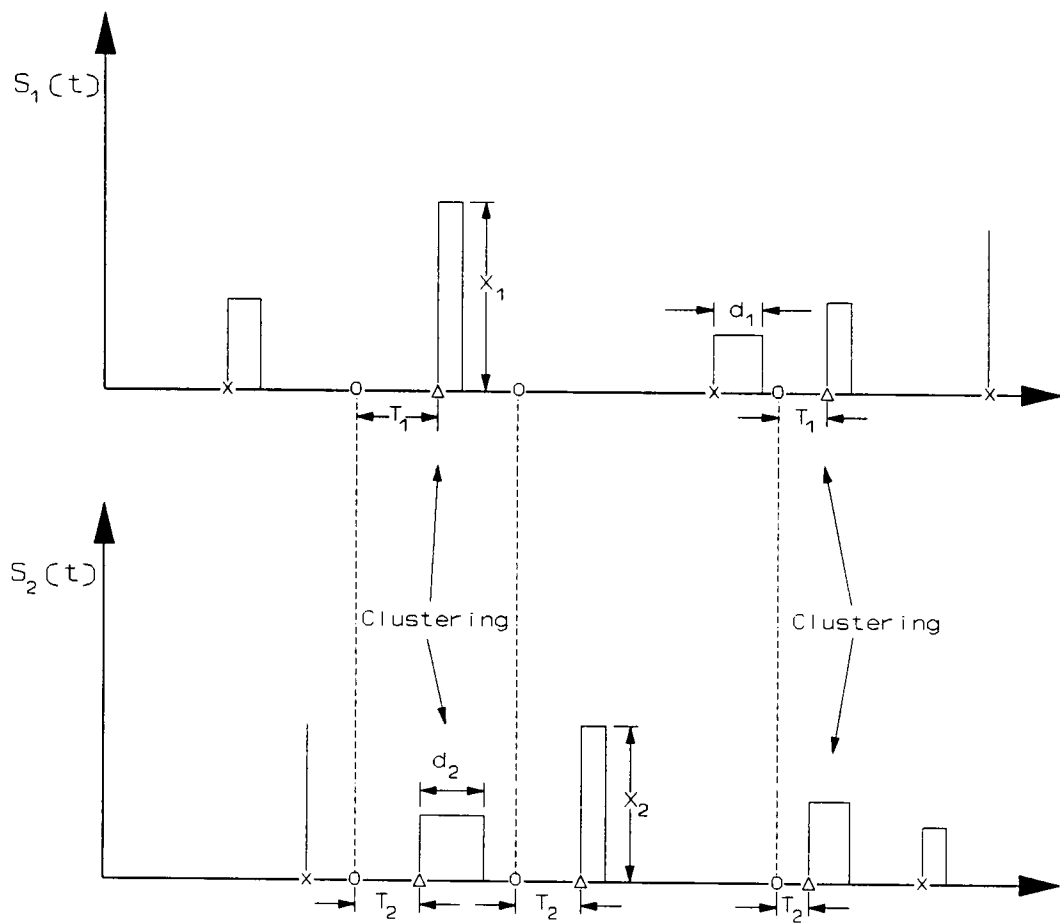
Both intensity and occurrence dependence may exist between snow loads and wind loads. Intensity dependence may be positive when wind causes snow to drift or negative when snow is removed by wind. This dependence would then be a function of roof geometry. Isyumov (1982), O'Rourke et al. (1982), and Templin and Schriever (1982) have examined dependencies of this type. Dependence of snow occurrences on wind exist in two forms, occurrence of each from the same storm and seasonal variations in each load. Occurrence dependence will be investigated in this research since the primary focus of this research is on occurrence and temporal statistics.

Wen and Pearce (1981a) have developed an intra-load clustering model as shown in Figure 6.1. This load model is characterized by the occurrence rate ρ of the parent generating process which produces the wind and snow occurrences, the random delay time of a particular process after the parent process has occurred (denoted T_i in Figure 6.1), and the parameters X_i and d_i which define the intensity and duration, respectively, of a specific wind or snow occurrence. The parent point process is considered to be a simple Poisson process. The occurrence of each load is taken as a simple Poisson point process, which jointly forms a multi-variate point process (Wen, 1990). The duration and intensity are modelled as Poisson renewal pulse processes with a mean duration and a specified intensity distribution function. The random delay time of a given snow or wind occurrence can be set to zero thus coinciding with the parent process. Hence, the load process that has its random delay time set to zero becomes the parent generating process.

If the delay times are modelled with an exponential distribution with small durations, the coincidence rate for the two loads is (Wen, 1990)

$$\lambda_{12} \approx \lambda_1 \lambda_2 (\mu_{d_1} + \mu_{d_2}) \left[1 + \frac{\rho_1 \rho_2 \rho}{\lambda_1 \lambda_2} \frac{1}{(a_1 + a_2)} \right] \quad (6.1)$$

where λ_1 is occurrence rate of the first load, λ_2 is the occurrence rate of the second load, μ_{d_1} is the mean duration of



- o Parent (generating) point process
- Δ Delayed point process
- x Noise process
- T_i (Random) delay time
- X_i Intensity given occurrence
- d_i Duration given occurrence

Figure 6.1 Intra-load Clustering Model (Wen and Pearce, 1981a).

the first load, μ_{d2} is the mean duration of the second load, p_1 and p_2 are the probability that a load has occurred, a_1 and a_2 are the respective mean delay times, and ρ is the occurrence rate of the parent process. Since wind and snow processes are clustered themselves, an extension of Equation 6.1 is needed to account for clustering in the intra-load model. The clustering effects would then be handled by the following equation (Wen, 1990):

$$\lambda_{12}^c = \lambda_1^c \lambda_2^c (\mu_{c_1} + \mu_{c_2}) \left[1 + \frac{p_1 p_2 \rho}{\lambda_1^c \lambda_2^c} \frac{1}{a_1 + a_2} \right] \quad (6.2)$$

where each term is defined as in Equation 6.1, except the parameters are now for clustered rather than individual occurrences.

Inherent in this model is the probability that snow and/or wind will occur given the parent generating process occurs. For a given parent generating process, potentially snow, wind, both, or neither actually occur. Hence, the probability of a wind or snow occurrence could be less than one. A thorough meteorological analysis would be required to obtain actual values for p_1 and p_2 . Thus, data will be analyzed from the viewpoint of simultaneous snow and wind occurrences from the same parent process. This results in setting p_1 and p_2 equal to one.

The intra-load clustering model would handle the dependence of snow and wind loads arising from the same storm.

Wind load data is recorded at much finer time increments than snow load data; therefore, snow load data that is recorded at time increments finer than one day are necessary. Local Climatological Data Monthly Summaries can be used to obtain water equivalent precipitation data for use in this load model. The data in these summaries are given at one-hour intervals. The water equivalent load data does not separate snow from rain loads; however, the data given at three-hour intervals specifies the type of weather that occurred within the given interval. Thus, hourly snowfall can be inferred from the data given in the monthly summaries. Also, snow depth measurements are made at 7:00 a.m each day to determine whether or not a daily water equivalent snow depth is measured for that particular day (i.e. a measurement is made if the depth is equal to or greater than 2 in.). Research by Belk (1988) has provided data on exact times of significant (i.e. greater than 20 knots) wind occurrences for nine sites. Rochester, NY, Detroit, MI, and Knoxville, TN are the three sites that are common to this research and that of Belk (1988). Two years of wind data were examined for Rochester and Detroit, while seven years of wind data were examined for Knoxville.

Data from these two sources were examined to find examples of joint occurrences that would correspond to the intra-load clustering model format. Figure 6.2 gives an example of a snow and wind joint occurrence for Rochester, NY

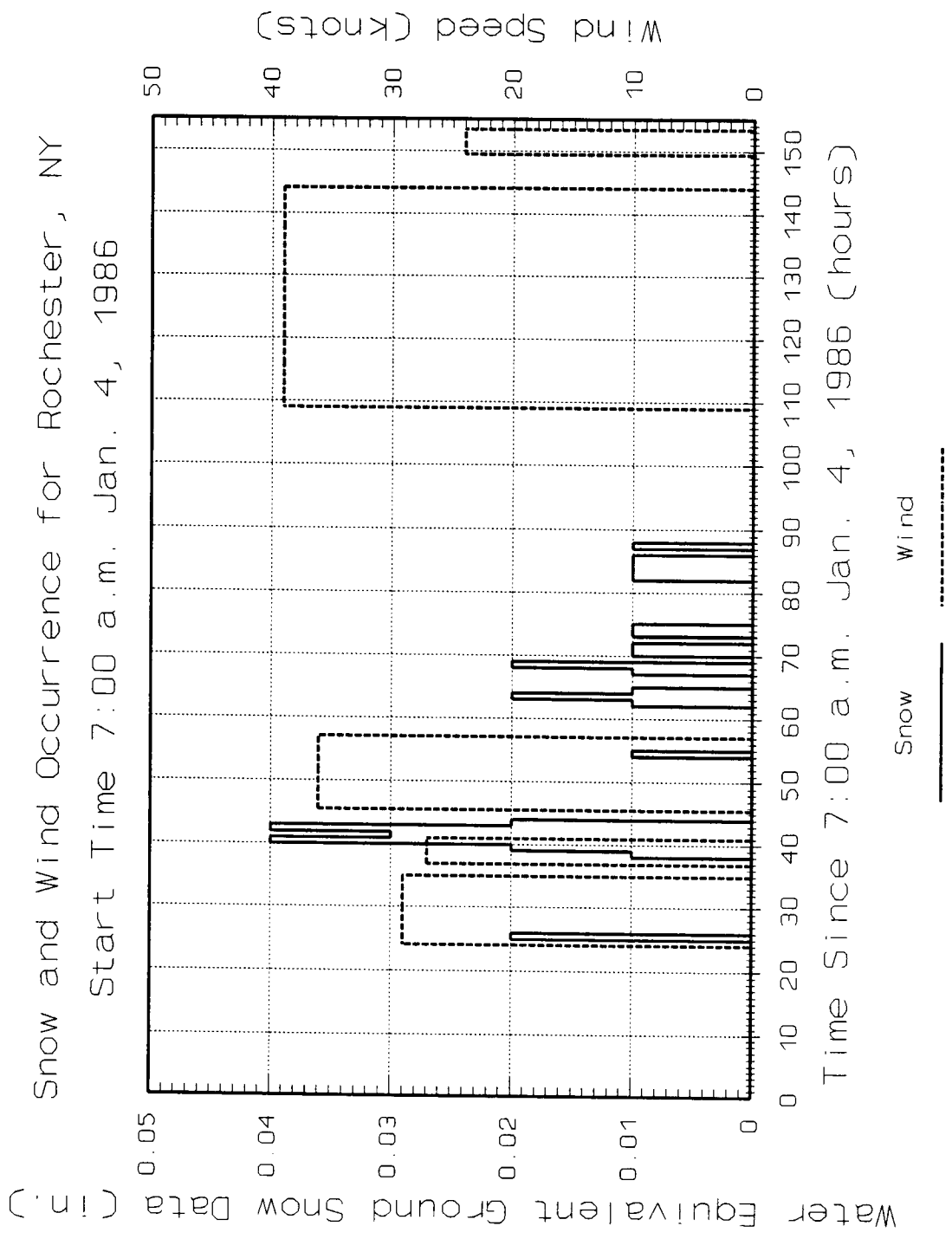


Figure 6.2 Snow and Wind Occurrence for Rochester, NY.

starting at 7:00 a.m. on January 4, 1986. Figure 6.2 is representative of actual snow and wind occurrences. The snowfall data points are actual water equivalent amounts of snowfall that occurred within a given hour. Note that the three wind occurrences on the left side of the graph are clustered with snow occurrences, while the wind occurrences on the right are not clustered with a snow occurrence. Thus, the snow and wind on the left are assumed to be from the same parent process, while the wind occurrences on the right are not.

Figure 6.3 graphs the occurrences for the same time period, but shows the cumulative snow as used in the snow model in Chapter 3. The snow occurrence is taken to be the parent process with a specific start time of 7:00 a.m. on January 4, 1986. The maximum intensity of the snow occurrence is 1.4 inches while the duration is 14 days. Three wind occurrences exist within the snow occurrence. However, only the first wind occurrence, which consists of three clustered winds, would have any dependence on the snow process as indicated by Figure 6.2. This clustered wind occurrence has a delay time of 1.00 days from the starting point of the snow process model. The intensity and duration of this wind occurrence are 36 knots and 1.376 days, respectively. The data from this occurrence would then yield one data point describing the process.

Thus, the first step in defining the intra-load

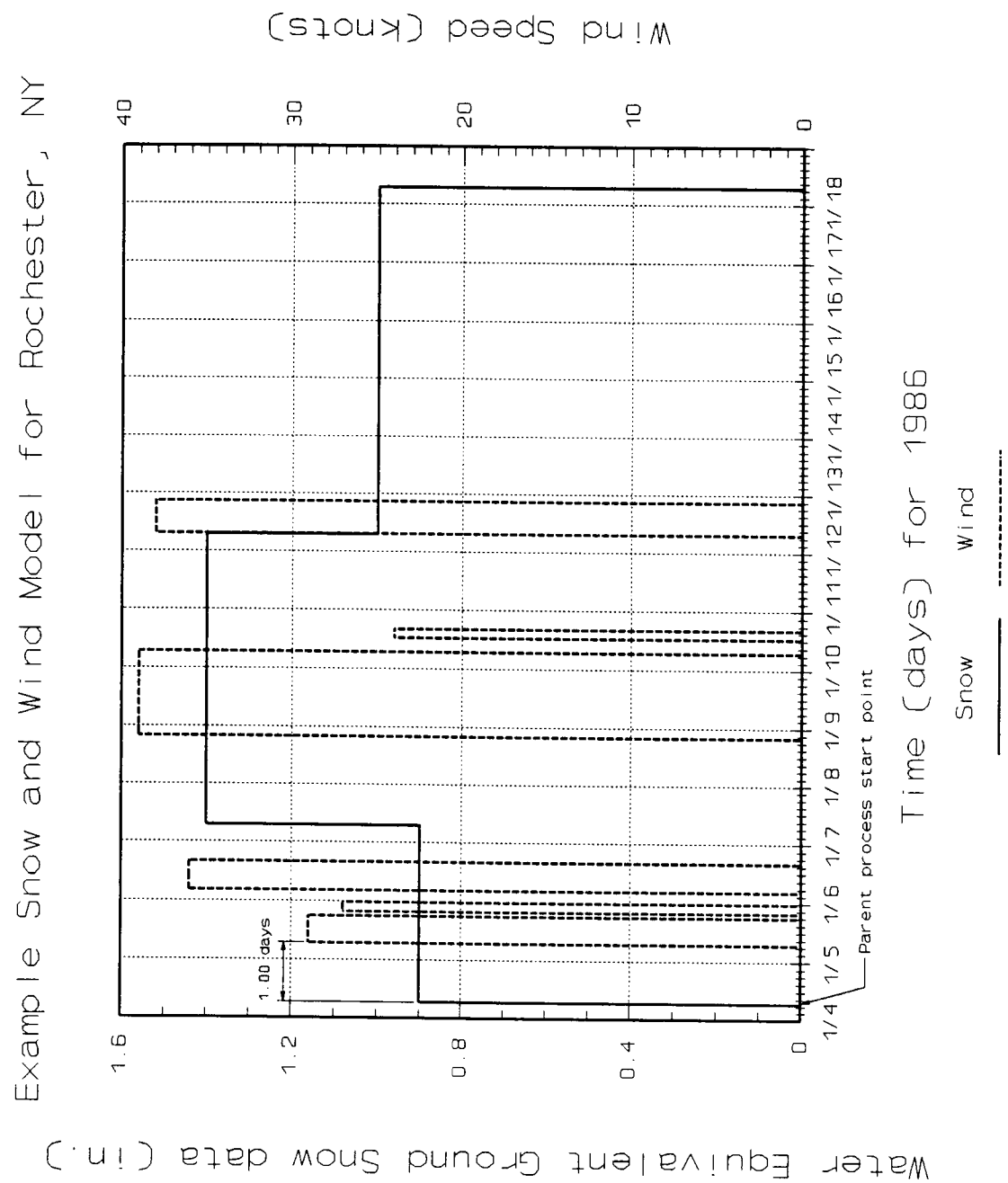


Figure 6.3 Example Snow and Wind Model for Rochester, NY.

clustering model is to examine hourly snowfall and wind occurrences to determine if the snow and wind processes were generated by the same parent process. If the two individual processes appear to be from the same parent process, a model containing the cumulative snow and the wind occurrence can be developed to determine the statistical parameters necessary to define the process. This two-step process can be extended to cover the length of time necessary to adequately define the intra-load clustering model.

Long term seasonal variations is the other form of occurrence dependence between snow and wind loads. Data from Belk (1988) indicate that there is a significant drop in wind occurrences during July, August, September, and October for Rochester and Detroit. Figure 6.4 shows the variation of wind occurrences for two years of wind data collected from continuous gust charts for Rochester and Detroit. Although the two sites differ somewhat in the specific occurrence rates for a given month, the general trend towards increased wind occurrences during the winter months holds true for both cities. Hence, correlation between the two loads will exist.

Rain loads or rain-on-snow loads are the other loads with which snow loads are correlated. Again, the focus is on occurrence statistics rather than combined intensities. Models developed by Colbeck (1977a, 1977b) determine rain-on-snow load intensities given the snow load is present and a rainfall occurs. Implicitly, the rain-on-snow load is

Wind Occurrence Variations for Rochester, NY
and Detroit, MI (Oct. 1, 1985-Sept. 30, 1987)

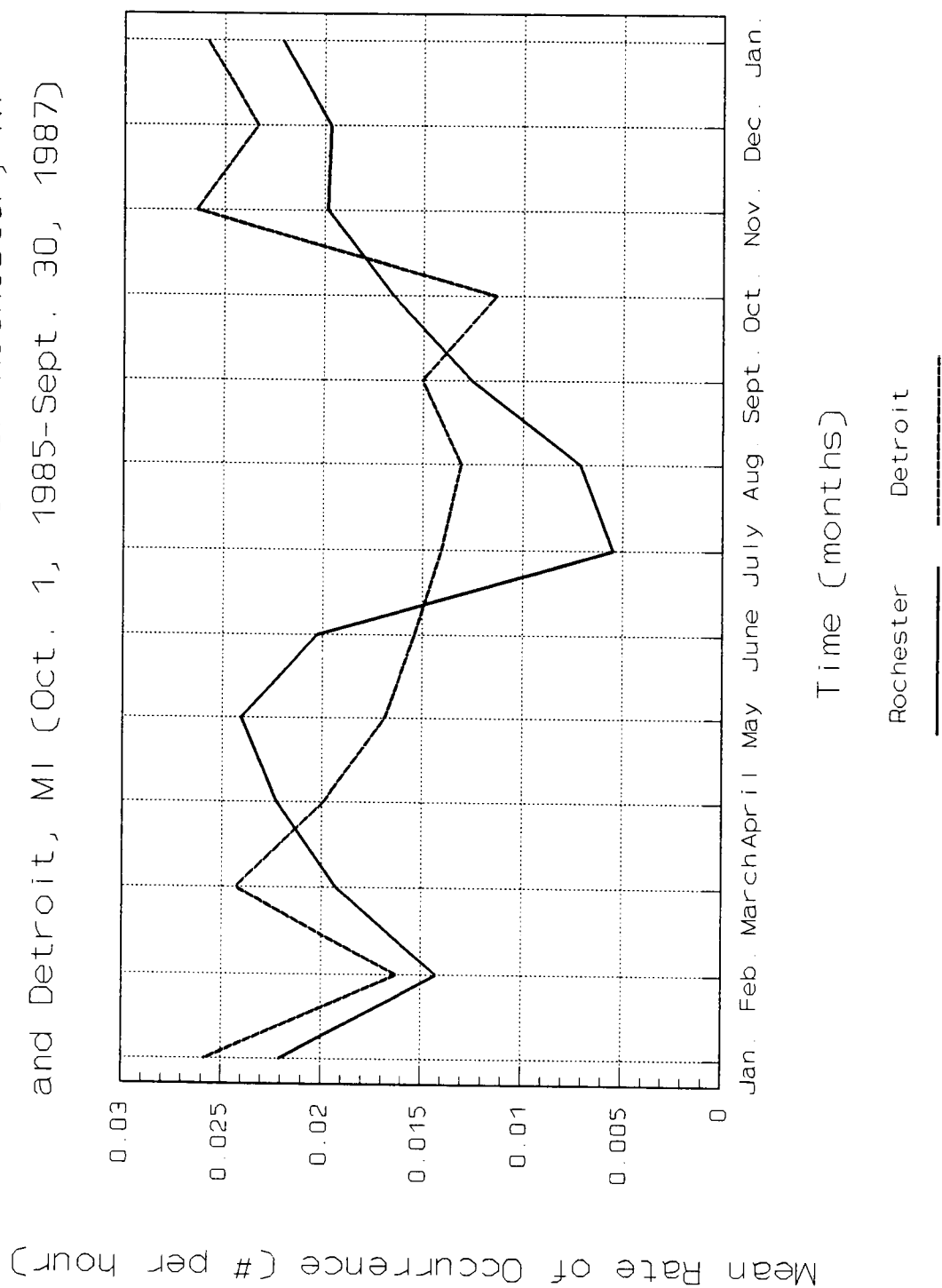


Figure 6.4 Wind Occurrence Variation for Rochester, NY and Detroit, MI.

accounted for when water equivalent ground snow load measurements are made. Since heavy rains may sift through the snow and drain off, these daily water equivalent measurements may not capture the maximum rain-on-snow load. Also, a building's roof slope may affect the roof rain-on-snow load which may not be the same as the ground rain-on-snow load (Ellingwood and O'Rourke, 1985).

In current design and load specifications, such as ANSI A58.1-1982 and ASCE /ANSI 7-88 revision, rain and snow loads are considered independent. The design equations involving the snow load S has the term $(L_r \text{ or } S \text{ or } R)$, where L_r is the roof live load and R is the initial rainwater load excluding the ponding contribution. Hence, "or" indicates that the designer does not need to include S and R acting together. However, Section 7.10 mentions rain-on-snow loads and gives recommendations in the Appendix for handling this load consideration. An intra-load clustering model of snow and rain could be developed in a fashion similar to the wind and snow load model by making use of Local Climatological Data Monthly Summaries.

CHAPTER 7

CONCLUSIONS

Typically, 20 years of daily water equivalent ground snow data have been collected for seventeen sites across the U.S. The data were modelled as a Poisson square wave pulse process. Statistics obtained include mean rate of occurrence, mean duration, and an appropriate distribution function for the intensity. Various distribution functions were fitted to the intensity data, with a Weibull distribution performing the best on average. Chi-square values and comparison of predicted values to well established 50-year snow loads provided the basis for this recommendation.

Various dependence calculations have been investigated. Occurrence dependence calculations have indicated that a clustered Poisson process is appropriate for modelling snow loads for use in load combination analyses. Dependence between intensity and duration can be ignored; however, intensity dependence within clusters should be considered in load combination analyses. A preliminary discussion of the correlation of snow with other loads has been provided through discussion and graphic representations.

BIBLIOGRAPHY

BIBLIOGRAPHY

- American Institute of Steel Construction (1986). "Load and Resistance Factor Design Specifications for Structural Steel Buildings."
- American National Standards Institute (1982). "Minimum Design Loads for Buildings and Other Structures." ANSI A58.1-1982.
- American Society of Civil Engineers (1988). "Minimum Design Loads for Buildings and Other Structures." Draft Copy, ANSI/ASCE 7-88.
- Ang, A. H-S., and Tang, W.H. (1975). *Probability Concepts in Engineering Planning and Design, Volume I: Basic Principles*, John Wiley and Sons, Inc., New York, NY.
- Ang, A. H-S., and Tang, W.H. (1984). *Probability Concepts in Engineering Planning and Design, Volume II: Decision, Risk, and Reliability*, John Wiley and Sons. Inc., New York. NY.
- Belk, C.A. (1988). "Wind Speed Modelling for Structural Load Combination Methods," thesis presented to the University of Tennessee, at Knoxville, Tennessee, in partial fulfillment of the requirements for the degree of Master of Science.
- Belk, C.A., and Bennett, R.M. (1991). "Macro Wind Parameters for Load Combination." *Journal of Structural Engineering*, ASCE, 117(9), 2742-2756.
- Boyd, D.W. (1961). "Maximum Snow Depths and Snow Loads on Roofs in Canada," Proc. 29th Annual Meeting Western Snow Conference, Research Paper 142, Division Building Research NRC 6312, NRCC, Ottawa, Ontario, 6-16.
- Colbeck, S.C. (1977a). "Roof Loads Resulting from Rain-on-Snow: Results of a Physical Model." *Canadian Journal of Civil Engineering*, 4, 482-490.
- Colbeck, S.C. (1977b). "Snow Loads Resulting from Rain on Snow." *United States Army Cold Regions Research and Engineering Laboratory Report* 77-12.
- Corotis, R.B., and Jaria, V.A. (1979). "Stochastic Nature of Building Live Loads." *Journal of the Structural Division*, ASCE, 105(ST3), 493-510.

- Corotis, R.B., and Tsay, W-Y. (1983). "Probabilistic Load Duration Model for Live Loads." *Journal of Structural Engineering*, ASCE, 109(4), 859-876.
- Ditlevsen, O., and Madsen, H.O. (1983). "Transient Load Modeling: Clipped Normal Processes." *Journal of Engineering Mechanics*, ASCE, 190(2), 494-515.
- Ellingwood, B., Galambos, T.V., MacGregor, J.G., and Cornell, C.A. (1980). "Development of a Probability Based Load Criterion for American National Standard A58." NBS Special Publication 577.
- Ellingwood, B., MacGregor, J.G., Galambos, T.V., and Cornell, C.A. (1982). "Probability Based Load Criteria: Assessment of Current Design Practice." *Journal of the Structural Division*, ASCE, 108(ST5), 978-997.
- Ellingwood, B., and O'Rourke, M. (1985). "Probabilistic Models for Snow Loads on Structures." *Structural Safety*, 2(4), 291-299.
- Ellingwood, B., and Redfield, R. (1983). "Ground Snow Loads for Structural Design." *Journal of Structural Engineering*, ASCE, 109(4), 950-964.
- Ghiocel, D., and Lungu, D. (1975). *Wind, Snow and Temperature Effects on Structures Based on Probability*. Abacus Press, Turnbridge Wells, Kent.
- Gray, D.M., and Male, D.W., eds, (1981). *Handbook of Snow: Principles, Processes, Management, and Use*. Pergamon Press, Toronto, Canada.
- Grigoriu, M. (1984). "Load Combination Analysis by Translation Processes." *Journal of Structural Engineering*, 110(8), 1725-1734.
- Hendrickson, E.M., Ellingwood, B., and Murphy, J. (1987). "Limit State Probabilities for Wood Structural Members." *Journal of Structural Engineering*, ASCE, 113(1), 88-106.
- International Conference of Building Officials (1988). *Uniform Building Code*.
- Isyumov, N. (1982). "Roof Snow Loads: Their Variability and Dependence on Climatic Conditions." *Structural Use of Wood in Adverse Environments*, Van Nostrand Reinhold Co., New York, NY, 365-384.

- Isyumov, N., and Davenport, A.G. (1974). "A Probabilistic Approach to the Predictions of Snow Loads." *Canadian Journal of Civil Engineering*, 1, 28-49.
- Larrabee, R.D., and Cornell, C.A. (1981). "Combination of Various Load Processes." *Journal of the Structural Division*, ASCE, 107(ST1), 223-239.
- Lindsey, S.D. (1988). Private Communication, Stanley D. Lindsey and Associates, Ltd., Nashville, Tennessee.
- McGuire, R.K., and Cornell, C.A. (1974). "Live Load Effects in Office Buildings." *Journal of the Structural Division*, ASCE, 100(ST7), 1351-1366.
- National Building Code of Canada (1989). National Research Council, Canada, Ottawa.
- O'Rourke, M.J., Redfield, R., and vonBradsy, P. (1982). "Uniform Snow Loads on Structures." *Journal of the Structural Division*, ASCE, 108(ST12), 2781-2798.
- O'Rourke, M.J., Speck, R.S., and Stiefel, U. (1985). "Drift Snow Loads on Multilevel Roofs." *Journal of Structural Engineering*, ASCE, 111(2), 290-306.
- O'Rourke, M.J., and Stiefel, U. (1983). "Roof Snow Loads for Structural Design." *Journal of Structural Engineering*, ASCE, 109(7), 1527-1537.
- O'Rourke, M., Stiefel, U., and Speck, R. (1984). "Snow Load for Earthquake Analysis." *Probabilistic Mechanics and Structural Reliability*, ASCE, 252-255.
- O'Rourke, M., Tobiasson, W., and Wood, E. (1986). "Proposed Code Provisions for Drifted Snow Loads." *Journal of Structural Engineering*, ASCE, 112(9), 2080-2092.
- O'Rourke, M.J., and Wood, E. (1986). "Improved Relationship for Drift Loads on Buildings." *Canadian Journal of Civil Engineering*, 13(6), 647-652.
- Pearce, H.T., and Wen Y.K. (1984). "Stochastic Combination of Load Effects." *Journal of Structural Engineering*, ASCE, 110(7), 1613-1629.
- Pier, J-C., and Cornell, C.A. (1973). "Spatial and Temporal Variability of Live Loads." *Journal of the Structural Division*, ASCE, 99(ST5), 903-922.
- Sachs, L. (1984). *Applied Statistics, A Handbook of Techniques*. Springer-Verlag, New York, NY.

- Sack, R.L. (1988). "Snow Loads on Sloped Roofs." *Journal of Structural Engineering*, ASCE, 114(3), 501-517.
- Sack, R.L. (1989). "Designing Structures for Snow Loads." *Journal of Structural Engineering*, ASCE 115(2), 303-315.
- Sack, R.L., Arnholtz, D.A., and Haldeman, J.S. (1987). "Sloped Roof Snow Loads Using Simulation." *Journal of Structural Engineering*, ASCE, 113(8), 1820-1833.
- Simiu, E., Changery, M.J., and Filliben, J.J. (1979). "Extreme Winds at 129 Stations in the Contiguous United States." *NBS Building Science Series No. 118*.
- Task Committee on Load and Resistance Factor Design for Engineered Wood Construction (1988). "Load and Resistance Factor Design for Engineered Wood Construction." ASCE, Pre-Standard Report.
- Taylor, D.A. (1979). "A Survey of Snow Loads on Roofs of Arena-type Buildings in Canada." *Canadian Journal of Civil Engineering*, 6(1), 85-96.
- Taylor, D.A. (1980). "Roof Snow Loads in Canada." *Canadian Journal of Civil Engineering*, 7(1), 1-18.
- Taylor, D.A. (1985). "Snow Loads on Sloping Roofs: Two Pilot Studies in the Ottawa Area." *Canadian Journal of Civil Engineering*, 12(2), 334-343.
- Templin, J.T., and Schriever, W.R. (1982). "Loads due to Drifted Snow." *Journal of the Structural Division*, ASCE, 108(ST8), 1916-1925.
- Thom, H. (1966). "Distribution of Maximum Annual Water Equivalent of Snow on the Ground." *Monthly Weather Review*, 94(4), 265-271.
- Tobiasson, W., and Redfield, R., (1983). "Snow Loads for the United States." *United States Army Cold Regions Research and Engineering Laboratory Report*, Hanover, N.H.
- Turkstra, C.J. (1970). "Theory of Structural Design Decisions," University of Waterloo, Ontario.
- Turkstra, C.J., and Madsen, H.O. (1980). "Load Combination in Codified Structural Design." *Journal of the Structural Division*, ASCE, 106(ST12), 2527-2543.
- Wen, Y.K. (1977). "Statistical Combination of Extreme Loads." *Journal of the Structural Division*, ASCE, 103(ST5), 1079-1093.

- Wen, Y.K. (1990). *Structural Load Modeling and Combination for Performance and Safety Evaluation*. Elsevier Science Publishers, Amsterdam, the Netherlands.
- Wen, Y.K. (1981), "Stochastic Dependencies in Load Combination." *Structural Safety and Reliability*. Elsevier Scientific Publishing Company, Amsterdam, 89-102.
- Wen, Y.K., and Kim, S.H. (1989). "Optimization of Structures Under Stochastic Loads." *New Directions in Structural Reliability*, University of Colorado, Boulder, CO, 299-314.
- Wen, Y.K., and Pearce, H.T. (1981a). "Stochastic Models for Dependent Load Processes." *Structural Research Series No. 489*, University of Illinois, Urbana, IL.
- Wen, Y.K., and Pearce, H.T. (1981b). "Recent Developments in Probabilistic Load Combination." *Probabilistic Methods in Structural Engineering*, ASCE, 43-60.

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